Effective Impulse Detector based on Rank-Order Criteria

Igor Aizenberg, *Member IEEE*, and Constantine Butakoff

***Abstract*— A new impulsive noise detection technique is presented here. Preserving edges and details in the process of impulsive noise filtering is an important problem. To avoid image smoothing, only corrupted pixels must be filtered. In order to identify the corrupted pixels, a new impulse detector is proposed. This detector is based on a comparison of signal samples within a narrow rank window by both rank and absolute value. It is efficient, very fast, and can be used with any filter (even iteratively), without smoothing an image.**

***Index Terms*—impulse detection, impulsive noise, median filter.**

I. INTRODUCTION

Impulsive noise filtering is an important field in image processing. As a rule, impulsive noise can significantly damage an image. A commonly used way to filter impulsive noise is median filtering [1]. Usually it is possible to completely eliminate impulsive noise using this classical approach. A significant disadvantage of median filtering is image smoothing. Other nonlinear filters, proposed for impulsive noise reduction (for example, rank-order filters [1]-[3], stack filters [1], weighted median filters [1], [2]), preserve image edges, but in general, the corresponding results are not good enough.

A good solution to this problem is noise detection implemented prior to filtering. If the corrupted pixels are identified and they are a priori known before filtering, then the filter can be applied only to these pixels. Several impulse detectors developed recently should be mentioned. In [4] a multi-pass filter, which is based on both global image statistics and statistics of samples inside the filter window, was proposed. The first pass of this algorithm marks each image sample as either "no filtering", "edges" or "noisy". The information collected on the first pass is used, as a set of parameters, for the second pass, which is weighted median filtering. A disadvantage of this filter is its orientation towards the "salt and pepper" noise model only. A more robust detector is proposed in [5]. This is also a two-pass method, which is based on an analysis of the so-called “edge flag image”, created on the first pass. An intelligent fuzzy filter [6] for heavily corrupted images and a filter based on long-range correlation in an image [7] should also be mentioned. The latter seeks to find a window similar to the one being processed and uses its information for filtering. In [8] different properties of recursive weighted median filters with negative weights are investigated. Another adaptive two-pass filter is developed in [9]. There are three more filters that are worth mentioning and they will be used later for comparison. The first one is the rational median hybrid filter [10], which uses several median filters and a rational decision rule to correct corrupted pixels. The second one is the Peak-n-Valley filter [11], which uses local maxima and minima to detect and correct impulses. The third one is the Switching Median Filter [12], which uses four one-dimensional Laplacian operators to detect impulses and to separate them from edges.

We want to propose here a new solution, an impulse detector that can be used with different nonlinear filters for effective detection of impulses in images containing impulsive noise. We will call it a Differential Rank Impulse Detector (DRID). This detector is based on two estimations. The first estimation is a comparison between the rank (the position in variational series) of the pixel of interest and the rank of the median. The second estimation is a comparison of the brightness values in the pixel of interest and in the pixel closest to the pixel of interest in variational series. It must be said that each of these estimations, if used separately, often misidentify pixels as impulses [13], [14]. They allow for the detection of extreme values of brightness in different ways and in combination they complement each other.

Many articles, published recently, for example the ones mentioned above, are mostly concerned with heavily corrupted images. By heavy corruption we mean the corruption of more than 20% and up to 90% of pixels. The case of a low corruption rate (below 15%-20% of corrupted pixels) is more interesting. This case in particular requires precise detection of corrupted pixels, because any misdetection will lead to loss of detail and smoothing of edges. This is why we want to pay

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I. Aizenberg is with the University of Dortmund, 44221 Dortmund, Germany (e-mail: igora@netvision.net.il)

C.Butakoff was with Neurotechnologies, Uzhgorod, Ukraine. He is now with the University of Zaragoza, Zaragoza 50018, Spain (e-mail: cbutakoff@ukr.net).

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special attention to the case of low corruption rate.

A remark should be made before venturing forth. The subject of the paper is noise detection. Because a detector cannot filter an image by itself, when we will speak about image filtering using the detector, we mean first that impulses are identified using this detector and then all the identified impulses are corrected by the median filter, although any other filter could be used instead. But since we will speak here about detection only, the values with which impulses are replaced are out of this paper's scope.

I. Impulse Detection

Since impulsive noise can change the brightness value of a pixel dramatically, an impulse can be identified by the height of its brightness jump in comparison with the surrounding pixels. Thus impulse detection can be reduced to the analysis of local image statistics within a window whose size is defined by a filter.

It is well known that the difference between the rank of an impulse and the rank of the median in a local window is usually large [1]. Let us consider the variational series (pixels from a filter window arranged by their value in ascending order) for a given filter window. The median is always located in the center of the variational series, while any impulse is usually located near one of its ends. This gives a natural and simple idea for impulse detection. This idea is based on a comparison between the rank of the pixel of interest and a threshold value:

$$\left(R(X_{ij}) \le s\right) \vee \left(R(X_{ij}) \ge N - s + 1\right), \tag{1}$$

where X_{ij} is the pixel of interest, $s>0$ is the threshold and N is the length of the variational series. $R(x)$ is the function that returns the rank (the position: from 1 to N) of an element x in the variational series. The sign "$\vee$" stands for disjunction. Therefore, if the condition (1) holds for some pixel X_{ij} then this X_{ij} is classified as corrupted by impulsive noise.

The detector (1) has been considered in [13]. It is very simple and gives good results. But it has a disadvantage, which makes the level of misdetection high. For every pixel corrupted by impulsive noise there exists an s such that the condition (1) holds, but the converse is not true, i.e. the condition (1) is no guarantee that a given pixel is corrupted by impulsive noise. The detector (1) takes into account only the ranks of signal values, but it does not consider these values themselves. This means that, even if it is usually possible to detect all the impulses by (1), many pixels may be classified as corrupted by mistake. So if a pixel is not corrupted, but still has the highest or lowest rank (e.g., if the pixel is part of an edge) it will be identified as an impulse. To overcome this disadvantage, it is necessary to take into account not only the rank of the pixel of interest, but also to consider its brightness value.

The first approach is to compare the pixel of interest to the median:

$$d_{ij} = \left| x_{ij} - \underset{i,j}{MED} \right|, \tag{2}$$

where $\underset{i,j}{MED}$ – is the median in a local window around the (i, j)th pixel. Equation (2) represents another simple detector, which can take an equivalent form: $\exp(d_{ij}) \ge \Theta_1$. The only difference is their reaction to the thresholds Θ and Θ_1. This detector also tends to detect edges as impulses and thus can be effective only when filtering heavily corrupted images. Both detectors (1) and (2) were considered in [14]. They form the basis for the development of the new detector that is described below.

We propose to consider here more accurate approach to analyzing a brightness value: calculating the difference with its closest neighbor in the variational series (the neighbor is chosen from the interval between the pixel of interest and the median):

$$d_{ij} = \begin{cases} \left| x_{ij} - Var\left[R(x_{ij}) - 1\right] \right| & \text{, if } R(x_{ij}) > \underset{i,j}{MED} \\ \left| x_{ij} - Var\left[R(x_{ij}) + 1\right] \right| & \text{, if } R(x_{ij}) < \underset{i,j}{MED} \\ 0 & \text{, otherwise,} \end{cases} \tag{3}$$

where $Var(k)$ returns a value of the pixel whose rank is k. In fact, (3) can be considered as an operator of differentiation.

From (1), (2), and (3) we can obtain the following formula:

$$\left(\left(R(X_{ij}) \le s\right) \vee \left(R(X_{ij}) \ge N - s + 1\right)\right) \wedge \\ \wedge \left(d_{ij} \ge \Theta\right) \tag{4}$$

where "$\wedge$" and "$\vee$" are the signs of conjunction and disjunction, respectively.

Depending on how d_{ij} is calculated, two different detectors are obtained. If d_{ij} is calculated according to (2), then the detector (4) is called an *enhanced rank impulse detector* (*ERID*). If d_{ij} is calculated according to (3), then (4) is called a *differential rank impulse detector* (*DRID*). In both cases, the detector (4) is based on a conjunction of two estimators, which allows for quite precise detection of impulses. It should be noted that for lightly corrupted images (up to 20% corruption rate) the DRID performs better than the ERID.

The choice of parameters s and Θ is based on the following empirical considerations. The parameter s depends on a corruption rate, because it determines the length of the subintervals on both ends of the variational series that should contain impulses. To ensure the complete detection of impulses, the value of s must be the smallest integer to make the intervals [0, s] and [N-s+1, N) contain all the impulses. For example, we can set s=1 for a 3x3 window if there is noise with a corruption rate below 5%, because there is a very high probability that every 3x3 local window contains no more than one corrupted pixel. Noise with a corruption rate of between 5% and 15% can be detected by means of a 3x3 window and s=2. For higher corruption rates it is necessary to increase s and the window size. For example, to cover the case of a corruption rate of higher than 30%, a 5x5 window must be chosen. To detect large spots, for example when two or three impulses stick together in an image, it is recommended to increase s. Generally in this case s must be such that the condition (1) will hold for the impulse closest to the median in the variational series. It is also very important to take into account that any filter in combination with the detector (4) can be applied to the image iteratively, while still preserving most of details from smoothing. In this case it is possible to detect impulses with greater precision (for example, experience shows that usually two iterations of filtering with s=1 give better results than one iteration with s=2). Iteratively decreasing s and applying the same filter, it is possible to eliminate the whole sequence of neighboring impulses in the variational series.

There is another way to choose the value of s. Since we consider uniformly distributed impulsive noise, the Bernoulli's formula can be used to calculate the probability that k impulses will appear in $n \times n$ window: $P_{n^2}(k) = C_{n^2}^k p^k (1-p)^{n^2-k}$, where p is the probability of pixel corruption. For example, for a 3x3 window and noise with the 15% corruption rate (p=0.15): $P_9(0)$=0.23, $P_9(1)$=0.36, $P_9(2)$=0.25, $P_9(3)$=0.1, …, $P_9(9)$=0.0000004. According to these probabilities s can be taken equal to the largest k, for which $P_{n^2}(k)$ is larger than some reasonable threshold. If this threshold is set to 0.1, then s=2.

To choose Θ with greater precision, it is necessary to have some estimate of the noise range. If the noise is closer to a pure "salt and pepper" model, then Θ can be made quite large, though $10 \le \Theta \le 20$ is usually sufficient for images with 8 bits per pixel. Although, if there is a series of impulses with similar brightness values in the window, then Θ can be made smaller (5 for example), without changing s, to ensure proper detection of impulses that are neighbors in the variational series. It should be mentioned that Θ can be constant and may not change from iteration to iteration (or even from image to image).

II. SIMULATION RESULTS

To check the efficiency of the proposed solutions, the test image (Fig. 1a) was artificially corrupted by impulsive noise with corruption rates of 1%, 5% (Fig. 1b) and 20%, respectively. In all cases, we used uniformly distributed impulsive noise with the uniform distribution of its values between the minimal (0) and maximal (255) possible signal values. The images obtained were processed using the median filter with prior impulse detection according to the solutions presented above and using some other filters. To check the efficiency, two criteria are used. The first is the estimate of standard PSNR between the original clean image and the result of filtering. The second criterion is as follows. Let us compose an image, where the value of each pixel is equal to 1, if the pixel was corrected by a filter, and 0 otherwise. Let us call it *the filtered noise model*. Then let us create another image, which is the real *model of noise*. This model of noise has each pixel equal to 1, if the corresponding pixel of the image contains an impulse, and 0 otherwise. It is easy to create this model since the noise is artificial. The standard deviation between these models shows the precision of impulse detection. This criterion can also be used to see the level of edge smoothing, and it does not vary with the height of impulses.

The results are summarized in the Table I and Table II. The images of 5% impulsive noise filtering are presented in Fig. 1. It is easy to see that both of the solutions proposed in this paper give good results, especially for 1% corruption. Table II is especially important since it shows only the detection ability and not the correction ability. It shows that the detector (4) combined with different filters significantly decreases the number of corrected pixels.

III. CONCLUSIONS

A new impulse detector, the *differential rank impulse detector*, is developed in this paper. It provides good results for impulsive noise detection and elimination by the median filter (or by other filters that are usually used for impulsive noise removal), with minimal image smoothing. It is also fast and efficient in its computing implementation, and almost any filter combined with this detector can be applied iteratively without unnecessary image smoothing.

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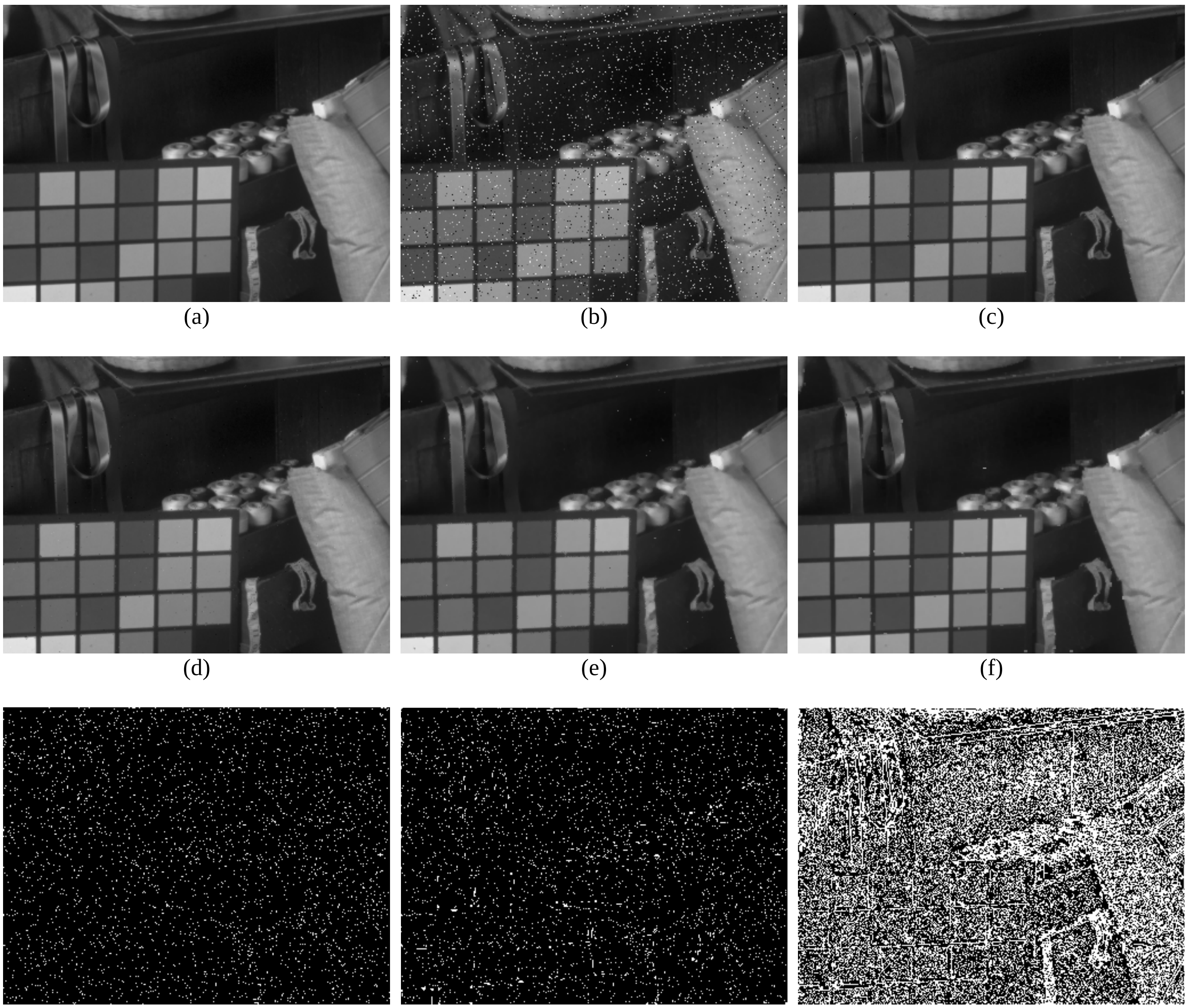
TABLE I
PSNR BETWEEN THE CLEAN AND FILTERED IMAGES

	1%	5%	20%
Noisy Image	26.91	20.83	15.11
Median with ERID	47.95	43.37	**36.64**
Median with DRID	**49.40**	**43.84**	35.24
Peak-n-Valley[11]	41.29	37.43	26.21
Rational Hybrid[10]	43.48	38.33	33.56
Switching Median Filter[12]	45.35	41.41	34.63

TABLE II
STANDARD DEVIATION BETWEEN THE NOISE MODELS

	1%	5%	20%
Median with ERID	0.050	0.086	0.153
Median with DRID	**0.041**	**0.073**	**0.152**
Peak-n-Valley[11]	0.591	0.591	0.632
Rational Hybrid[10]	0.553	0.641	0.697
Switching Median Filter[12]	0.076	0.120	0.288



(a) (b) (c) (d) (e) (f) (g) (h) (i)

Fig. 1. Impulsive noise filtering by different filters. 3x3 window had been used. Other parameters are written as "*s*=3,2,1,1 and Θ =40,40,5,5", which means that for the first iteration *s=3* and Θ =40 were used, for the second one *s*=2 and Θ =40, then *s*=1 and Θ =5, etc.

(a) – Clean image; (b) – Image with 5% impulsive noise; (c) – Median filter with DRID, 4 iterations, *s=3,2,1,1* and Θ *=40,40,5,5* (according to each iteration); (d) – Switching median filter[12], 3 iterations, *T=70*; (e) – Rational Hybrid Median[10], *h=2*, *k=0*; (f) – Peak-n-Valley[11]; (g) Pixels where (c) differs from clean image (a); (h) Pixels where (d) differs from clean image (a); (i) Pixels where (e) differs from clean image (a).